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Fuzzy Entropy-Based State of Health Estimation of $LiFePO_4$ Batteries Considering Temperature Variation

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***Abstract*—Sample entropy (SE) has been used as a feature to estimate the state of health (SOH) of batteries as it can capture the voltage variation during battery degradation. However, because the Heaviside function is used to access similarity in the definition of SE, SE is sensitive to parameter selection. Hence, the SE shows an obvious change when the battery is aged at different conditions (e.g., temperatures), leading to a decrease in the estimation accuracy. By introducing the concept of fuzzy membership, the generalized version of SE, fuzzy entropy (FE) is weak influenced by parameters and test condition. Therefore, the FE is proposed as a feature to estimate the SOH of battery in terms of aging temperature variation. The FE-SOH is used as the input-output data pair of support vector machine, then the single-temperature model, full temperature model, and partial-temperature model are established. Compared with the SE-based method, FE-based method not only has better estimation accuracy, but also decreases the dependence on the size of training data. Finally, the effectiveness of the proposed method is verified using experimental results.**

***Keywords*—Lithium-ion battery, State of health estimation, Aging temperature variation, Fuzzy entropy, Sample entropy, Support vector machine.**

I. INTRODUCTION

Lithium-ion batteries have been widely applied in both electric vehicles and energy storage systems [1]. However, one of the main concerns in these applications is the battery's degradation (i.e., capacity fade and power decrease), which is inevitable during practical use. Hence, it is necessary to know the batteries' state of health (SOH) in order to ensure the reliable operation of the battery [2]. Among the existing research, the estimation methods mainly consists of the following three categories: the direct assessment method, the adaptive filter-based method, and the data-driven method [3-4]. Since the capacity is the integral of current with respect to time, the capacity degradation of battery can be obtained directly using the measured current [5]. Establishing the relationship between the internal resistance and the battery capacity is also a direct tool to estimate SOH. Mu et al. [6] establish a fractional order impedance model using EIS, which can separate the electrochemical reactions in a nondestructive manner and track the variations of the battery's performance under different SOHs. Some adaptive filters, such as the Kalman filter [7] and partial filter [8], are designed based on the electrochemical models or equivalent-circuit models of battery. The model is first transformed into the stat-space form and then the model parameters are updated and the state variables are estimated by the designed filter. Finally, the state variables associated with the aging level can be obtained. Data-driven methods, such as neural network [9], support vector machine (SVM) [10], and Gaussian progress regression [11] are gaining increasing interest for battery SOH estimation due to their flexibility and being model-free.

Because incremental capacity peaks [12], the similarity of the voltage profiles [13], or the knee points of voltage response to pulse test [10] contain plentiful information of battery aging, they are used as features for parameterizing SOH estimation algorithms. However, such kinds of features are extracted from the voltage curves under full charging and full discharging process, which is not convenient in real application due to time constraints. Therefore it is necessary to find an effective feature that not only contains enough degradation information of battery but it is easily accessible. Sample entropy (SE), as a powerful statistic for measuring the complexity of a signal, has been used for SOH estimation. Li et al. [14] monitored the surface temperature of batteries during the charging process, and found that the SE is related to the battery degradation. In order to shorten the experimental time, Hu et al. used the voltage data under a short pulse test for SE calculation, then the SOH was estimated by the polynomial fitting method [15] and the sparse Bayesian predictive modeling [16]. Sui et al. [17] studied the effect of dataset on the accuracy of SE-based SOH estimation method, and they found that the pulse test which makes the SOC enter into the polarization zone is helpful to reduce the estimation error.

Because the aging temperature has a significant effect on the battery's degradation behavior [18], the SOH estimation considering the temperature variation is worth to be studied. In the aforementioned works, the temperature was only changed in the performance tests (for SE feature extraction), while the entire aging process is maintained at a constant temperature. The effect of aging temperature on the battery parameters is not contained in the model, so that the proposed model is not necessarily applicable to estimation SOH at different temperatures and subsequently at different aging conditions.

In this paper, batteries were aged at different temperatures and the performance test (also for SE extraction) was conducted at the same temperature condition, i.e., 25°C. As a result, the obtained SE is sensitive to aging temperature variation, and the accuracy of SE-based method will decrease. Fuzzy entropy (FE) is an improved measure of time series regularity, because it defines the vectors' similarity based on fuzzy calculation and vectors' shapes [19]. Hence, FE of voltage is more consistent and robust to temperature variation. In this paper, to improve the SOH estimation accuracy for different aging temperature conditions, FE is introduced to capture the variation of the voltage. The FE, SOH, together with temperature are used as input variables. Then the FE-SOH relationship at different temperatures are established utilizing the SVM technique. For comparison purposes, the SE-based model is also established, and the framework of the proposed method is shown in Fig. 1. Finally, aging tests are

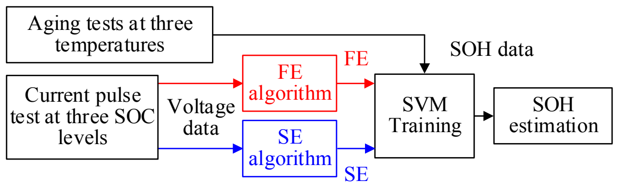


Fig. 1. Schematic diagram of the proposed algorithm.

conducted on six $LiFePO_4$ batteries at three temperatures for validating the proposed method for SOH estimation.

II. FUZZY ENTROPY-BASED SOH ESTIMATION METHOD

A. Sample entropy and fuzzy entropy algorithm

The specific algorithms of FE and SE are described in Fig. 2. SE is the negative natural logarithm of the conditional probability where a dataset of length N, having repeated itself for m points within a boundary, will also repeat itself for $m+1$ points. The Heaviside step function with a rigid boundary r is used in similarity degree computation [19]. Based on the definition of similarity of SE, the data segments with distances lower than r are considered as positive matches, while others are rejected and not considered for the calculation. In this case, two points that are far apart but within the boundary are treated equally, while the points just outside the boundary are left out. Thus, SE is sensitive to parameter variation and cannot reflect the information contained in the data accurately [19]. The FE improves the SE by using an exponential function as fuzzy function to describe the similarity degree of two vectors. The fuzzy function can obtain more details, making FE a more accurate definition than SE. Besides, another main improvement of FE calculation is that the mean of the match templates is removed in the step of vectors generation, Therefore, the vectors' similarity in FE is measured based on their shapes rather than their absolute coordinates. As a result, FE owns stronger relative consistency.

B. SOH estimation based on SVM

SVM is an effective method to deal with nonlinear regression problems, which uses kernel technique to map features vectors to high-dimensional space [10]. A SVM model is established to capture the nonlinear relationship between features (i.e., FE and SE) and SOH. The objective of the SVM is to find the optimal coefficients $\mathbf{w}$ and b on the basis of the following constrained optimization problem,

$$\begin{aligned} &\min_{w,b} \ \frac{1}{2}\mathbf{w}^T\mathbf{w} \\ &s.t. \quad \mathbf{y}_i - \mathbf{w}^T\cdot\mathbf{x} - b \le \varepsilon \\ &\qquad\ \ \mathbf{w}^T\cdot\mathbf{x} + b - \mathbf{y}_i \le \varepsilon \end{aligned} \tag{1}$$

After solving equation (1), the SOH estimation function is obtained as:

$$f(\mathbf{x}) = \sum_{i=1}^{n}(\alpha_i^* - \alpha_i)K(\mathbf{x}_i,\mathbf{x}) + b \tag{2}$$

where $K(\mathbf{x}_i, \mathbf{x})$ is the radial basis function kernel with the form of $K(\mathbf{x}_i,\mathbf{x}) = \exp\left(-\|\mathbf{x}_i - \mathbf{x}\|^2/2\gamma\right)$, α_i^* and α_i are Lagrange multipliers.

III. EXPERIMENTAL TEST AND AGING DATA

The parameters of the tested $LiFePO_4$ batteries are listed in Table I. As shown in Fig. 3, the test setup consists of a FuelCon battery test station, which is used to perform the reference measurements and obtain the test profiles, and a host computer which is used for controlling the test station and collecting the data. Six cells, numbered C.1 to C.6, were connected to the chamber which provides a constant temperature test environment. The whole test consists of two

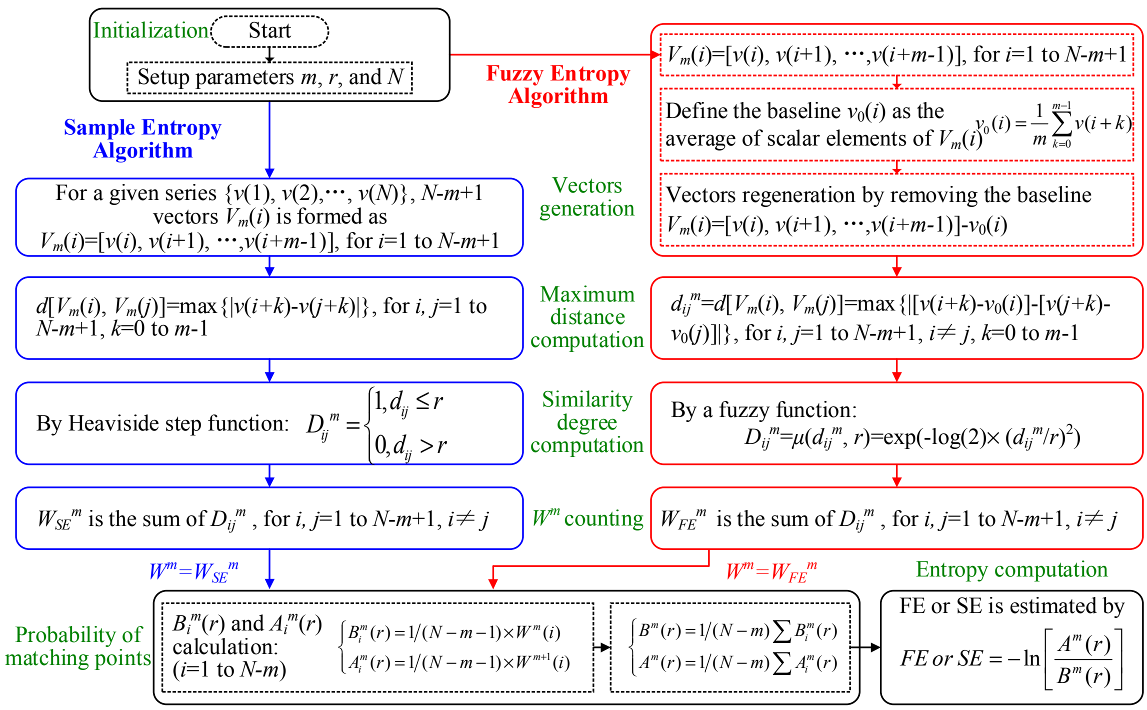


Fig. 2. Flowchart of fuzzy entropy and sample entropy algorithms.

parts: the aging test and the performance test, as shown in Fig. 4. During the aging test, batteries were stored with 50% state of charge (SOC) and at three different calendar temperatures, i.e., 55℃, 47.5℃, and 40℃, respectively (two batteries were tested at each temperature). After each one-month of calendar aging, the performance tests were conducted. Firstly, the battery capacity was measured at 25°C using a 1C-rate constant current discharging procedure. Based on these measurements, the capacity fade curves can be obtained and the SOH is calculated as the ratio between the current maximum available capacity and the initial maximum available capacity, as shown in Fig. 5. Then these cells were charged at 25℃ with a 1C-rate constant current to 20% SOC, 50% SOC and 80% SOC, respectively. At each SOC level, a 4C-rate (i.e., 10A) pulse test was conducted and the voltage responses were used for FE/SE extraction. As for an example, Fig. 6 shows the collected voltage datasets of the training cell numbered C.3. All the aging tests stopped when the batteries' capacity fades by 20% of the initial value where the batteries are considered to reach their end-of-life.

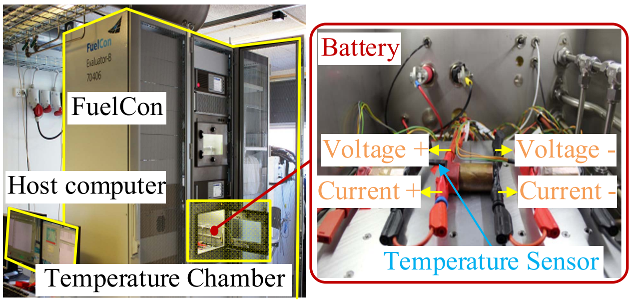


Fig. 3. Experimental setup.

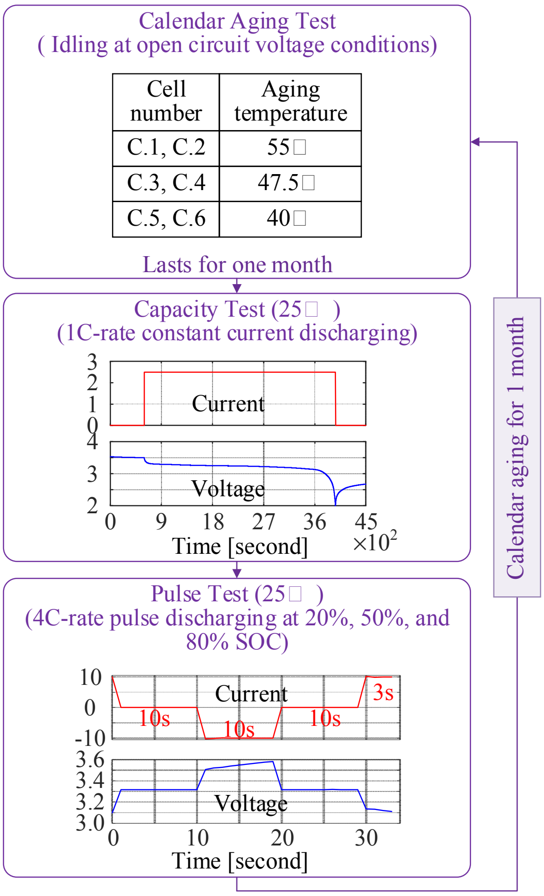


Fig. 4. Flowchart of the test schedules.

TABLE I. THE DATASHEET OF THE $LiFePO_4$ BATTERY.

Item	Value
Nominal voltage	**3.3 V**
Charge voltage	**3.6 V**
Cut-off voltage	**2.0 V**
Nominal capacity	**2.5 Ah**
Maximum continuous charge current	**10 A**
Maximum continuous discharge current	**50 A**

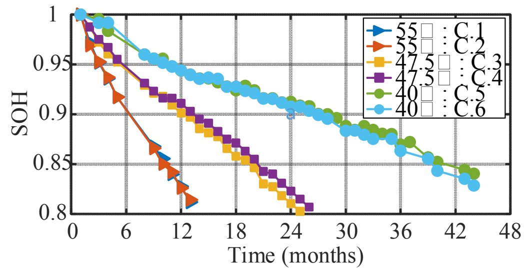


Fig. 5. SOH curves of the tested six cells during the calendar aging at 55 ℃, 47.5 ℃, and 40 ℃.

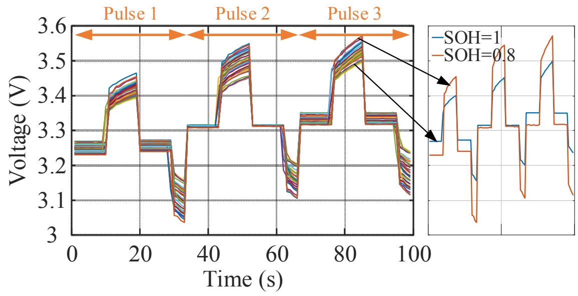
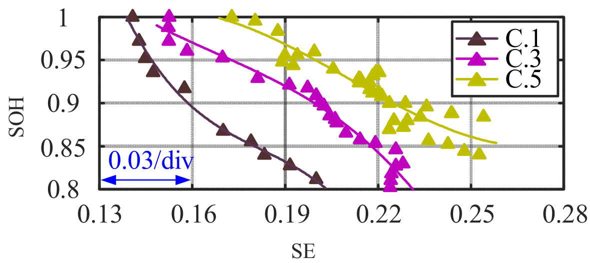
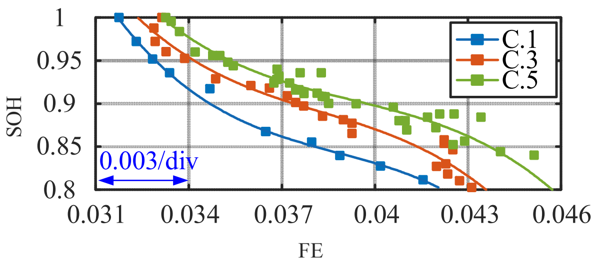


Fig. 6. Voltage datasets obtained during the current pulse tests (as for an example, the aging temperature is 47.5 ℃).

The tested cells were divided into a training group (C.1, C.3, and C.5) for establishing the entropy-based estimator, and a validation group (C.2, C.4, and C.6) for estimation accuracy verification. Based on the minimization of the maximum entropy relative error as described in [17], the parameters of m, r, N were taken as 3, 0.04, 99 for FE algorithm, and 3, 0.08, 99 for SE algorithm. The obtained SE/FE values at three aging temperatures are shown in Fig. 7, and it can be seen that SE (as seen in Fig. 7(a)) varies obviously with temperature, while FE (as seen in Fig. 7(b)) maintains more relative consistency over a wide temperature range.



(a)



(b)

Fig. 7. Entropy feature curves at 55 □, 47.5 □, and 40 □. (a) Sample entropy, (b) Fuzzy entropy.

The root-mean-squared error (*RMSE*) and the mean absolute percentage error (*MAPE*) are used to evaluate the performance of the proposed method, which are defined as:

$$RMSE = \sqrt{\frac{1}{N_T}\sum_{i=1}^{N_T}\left(S\hat{O}H_i - SOH_i\right)^2} \tag{3}$$

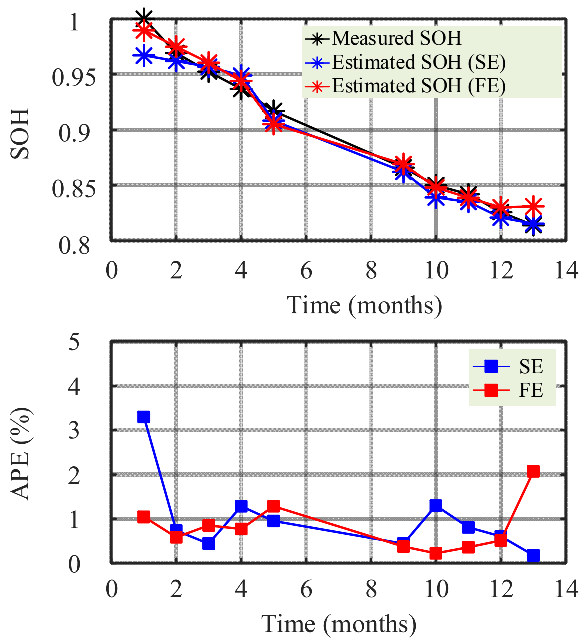
$$MAPE = \frac{1}{N_T}\sum_{i=1}^{N_T}\left(\frac{\left|S\hat{O}H_i - SOH_i\right|}{SOH_i}\times 100\%\right) \tag{4}$$

where N_T is the total number of validation data, $S\hat{O}H_i$ and SOH_i is the estimated SOH and the real SOH of the *i*th validation data point, respectively.

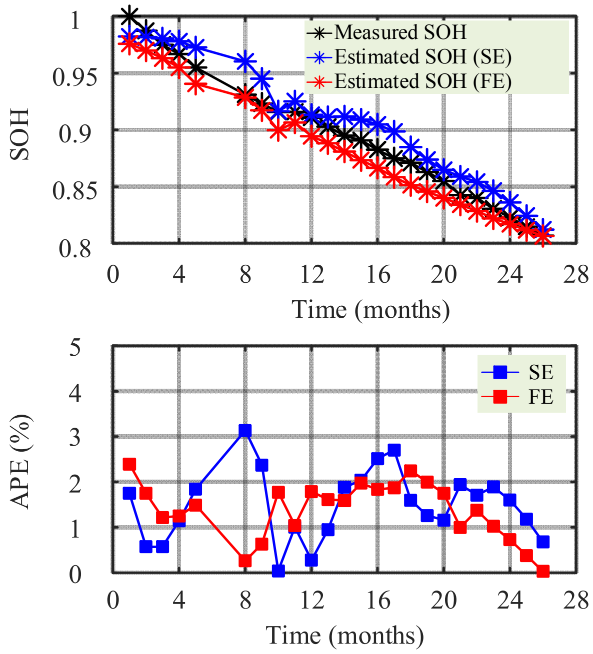
IV. SOH ESTIMATION RESULTS

A. Single-temperature model

Three single-temperature models are established separately for 55□, 47.5□, and 40□, respectively. The input-output pairs only contain the data at one temperature and the model is validated by aging data of another cell at the same temperature. The SOH estimation results are shown in Fig. 8, and the comparison results between SE-based and FE-based method are shown in Fig. 9.



(a)



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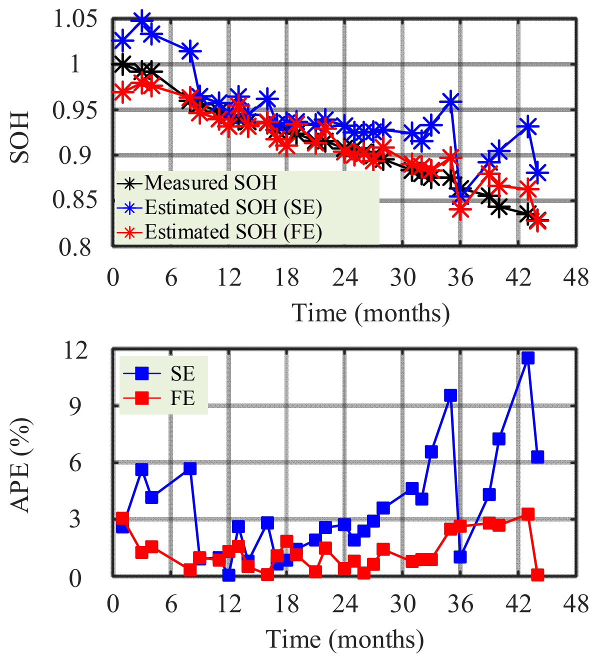
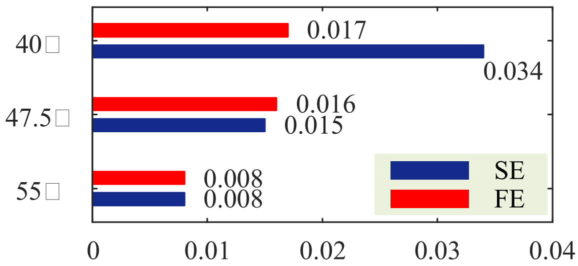


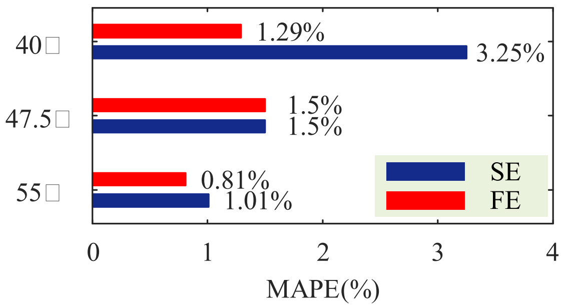
(c)

Fig. 8. SOH estimation results using single-temperature models (a) C.2 at 55ºC, (b) C.4 at 47.5ºC, (c) C.6 at 40ºC.

It can be seen from Fig. 8 that single-temperature models at high temperature (i.e. 55□ and 47.5□) have better estimation accuracy no matter which feature is used. However, at the lower temperature (i.e. 40□), the SE-based method shows a big fluctuation and its APE is more than 3%. The RMSE and MAPE of SE-based method are also about twice of that of FE-based method (as shown in Fig. 9). When using FE as the feature for SOH estimation, smaller APE values are obtained at most of the validation points, while the MAPE for the FE-based method is kept less than 1.5% over a wide temperature range.



(a)



(b)

Fig. 9. Estimation errors of single-temperature models. (a) RMSE, (b) MAPE.

B. Full-temperature model

In order to generalize the SOH estimation model at different temperatures, the full-temperature model is established. All the feature-SOH data pairs at three temperatures are used for model training, and the estimation results can be seen in Fig. 10. As it can be observed, the low temperature affects the estimation accuracy of SE-based method, while the APE of FE-based method is steadily kept less than 4%. As seen in Fig. 11, the RMSE and MAPE is 0.017 and 2.1% for SE-based method. Using FE as feature, both errors are reduced and they are 0.016 and 1.36%.

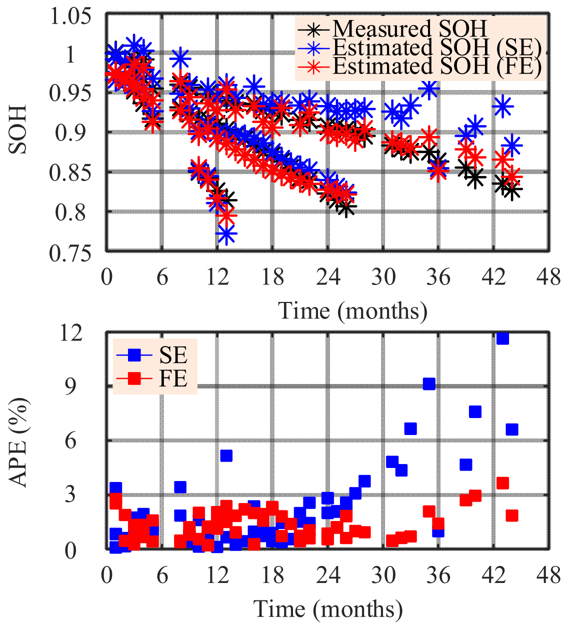
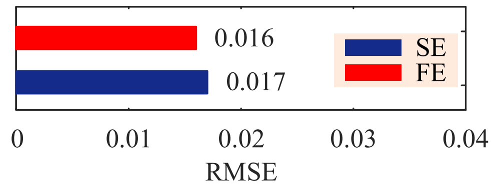
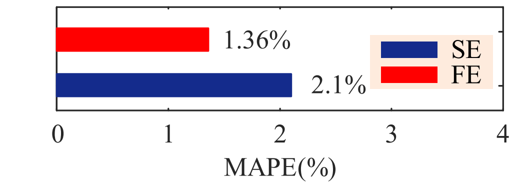


Fig. 10. Estimation results of full-temperature model.



(a)



(b)

Fig. 11. Estimation errors of full-temperature model. (a) RMSE, (b) MAPE.

C. Partial-temperature model

In the partial-temperature model, the validation temperature is not contained in the training process. For example, the training data contain the maximum temperature and the minimum temperature, and the estimation results for the battery aged at the intermediate temperature (i.e. C.4 at 47.5□) are shown in Fig. 12. Compared with SE-based method, the RMSE (as seen in Fig. 13) is reduced from 0.012 to 0.011, and MAPE decreases from 1.15% to 0.9%. It is also worth noting that the partial-temperature model is more accurate than the single-temperature model in estimating C.4 at 47.5□ (compared with Fig. 12 and Fig. 8(b)), which demonstrates that the FE-based method is more robust to temperature variation and relies on less training data.

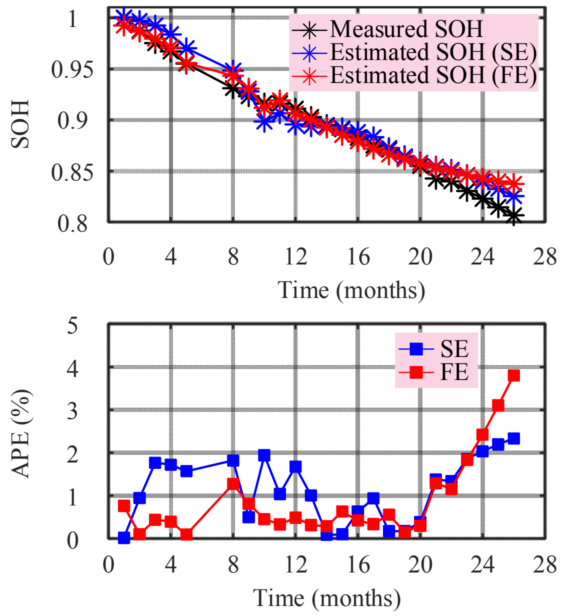
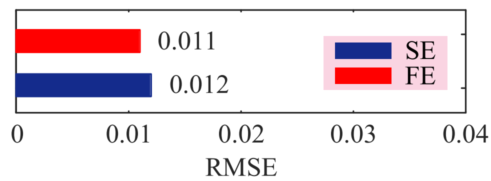
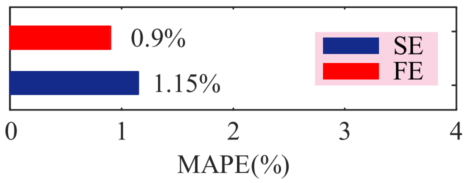


Fig. 12. Estimation results of partial temperature model for C.4.



(a)



(b)

Fig. 13. Estimation errors of partial temperature model for C.4. (a) RMSE, (b) MAPE.

V. CONCLUSIONS

This paper investigates the effect of aging temperature (which has a great impact on the battery degradation behavior) on the SOH estimation accuracy of SE-based method, and the aging data at three temperatures from six battery cells are used for model training and validation. The experimental results show that the FE-based model is less sensitive to battery aging conditions, and FE is more suitable for battery SOH estimation compared with SE. By using the temperature as the input variable, the single-temperature models, full-temperature model, and partial-temperature model are established using the SVM technique. Based on the single-temperature models and the full-temperature model, it was concluded that SE cannot accurately reflect the age of the battery at relatively low temperature (i.e. 40□), resulting in a big fluctuation in estimation error. In order to improve the estimation accuracy, the FE of voltage as a feature is proposed in this work. The results shows that the APE of FE-based method is less than 1.5% over a wide temperature range because FE contains more details of the battery voltage variation. Based on the partial-temperature model, FE still shows a better accuracy when decreasing the size of training data. Hence, FE-based method relies on less training data when aging temperature is taken into account for SOH estimation.

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